Understanding Investor behavior and it's implications on Capital Markets - The Indian Context

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Abstract

The paper proposes a dynamic factor model to augment the conventional three factor Fama and French – CAPM, by introducing two distinct latent variables which constitute investor behavior i.e. market sentiment and herding. Our analysis suggests that both factors significantly impact the asset pricing. Also, the herding factor portrays an erratic behavior during the crisis period whereas sentiment remains persistent across time.

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1. Introduction

Market dynamics are governed by various factors, behavioral aspects of individual participants being one of them. The debate emerges as to what extent and how, such behavioral tendencies aggravate price fluctuations. Robert Shiller postulates that people who interact with each other regularly tend to behave and think similarly, a phenomenon often called "Herd behavior". It describes a group of individuals who act to imitate the decisions of others or market in general without paying any attention to their own beliefs or information (Bikchandani and Sharma, 2000), as they believe that the others have information that justifies their actions (Shiller 1995). Such behavior has significant repercussions over the financial markets, for which reason we intend to study these aspects in context to the recent financial crisis of 2007-2008.

A growing body of work has developed over the years, which have examined the herding behaviour across different scenarios. The theoretical models of herding behavior have been developed by Bhikchandani and Sharma (1992), Scharfstein and Stein (1990) and Devenow and Welch (1996). While the empirical studies have focused on testing herding in various events including cross country and cross market studies, Chan, Cheng and Khorana (2000), analyzed the herding behaviour in the US, Hong Kong, South Korea, Taiwan, and Japanese stock markets and have concluded against the existence of pervasive herding behaviour for most of their sample.

Christie and Huang (1995) and subsequently, Chang et al (2000), first propounded the idea of empirical modeling of herd behavior using CH and CCK models, respectively. They used the cross sectional standard deviation (CSSD) and cross sectional absolute deviation (CSAD) across stock returns as a measure of average proximity of individual returns to the realized market return. Hwang and Salmon (2013) under similar guidelines extend their model to measure and capture the herding by studying dispersion in CAPM betas of assets. They separate adjustment to fundamentals, and herding due to market-wide sentiment by looking at variabilities in factor sensitivities.

Our study distinctively brings new perspective in the empirical study of herding behavior. First, the current literature hardly distinguishes between the market wide sentiments and herding, we propose a state space based dynamic factor model to extract the latent variables, depicting the market sentiment and herding for the Indian equity market. We consolidate our intuition into a dynamic factor model which allows for dynamic interaction of influential factors influencing assets across the markets. Second, the factors help market practitioners to understand and predict the investor trend patterns alongside market fluctuations.

We assess our model taking Indian Capital Markets as a benchmark and further checking its performance by testing it over the US markets. Over the years, India has emerged as one of the most favored destinations for foreign investors among the developing markets with one of the highest market capitalization. Since the liberalization of capital market in 1991, FII's investment in Indian equity market has crossed $60 billion. The FII investment prospects for India are very bright considering the inherent advantages that the country has and its potential to absorb capital for its development and growth. Therefore, given the increasing importance of the Indian equity market as the most favored destination it is imperative for the Indian regulator to keep a constant vigil on herding in the market.

The paper follows with an explanation of methodology in the next section. Second, we mention the data used for our analysis, followed by estimation of results and their interpretation. Finally, the last section concludes the paper.

2. Methodology

The CAPM model in its most generic form determines the rate of return of an asset, taking into account the market risk, also called the systematic risk. Researchers over the year have proposed various factors which can affect returns. Fama and French (2004), have further augmented this generic version by introducing a three factor model which claims to capture almost 90% of price fluctuations.

We start by considering that the portfolio returns are biased owing to behavioral dynamics of the market players. We assume that excess market returns $E_t^s(r_{mt})$ and individual asset portfolio returns $E_t^s(r_{it})$ are biased in the following manner:

$$E_t^s(r_{it}) = E_t(r_{it}) + \delta_{it}$$

$$E_t^s(r_{mt}) = E_t(r_{mt}) + \delta_{mt}$$ [1]

where δ_{it} and δ_{mt} represent the bias. For consistency we also require $\delta_{mt} = E_c(\delta_{it})$ where $E_c(.)$ represents the cross-sectional expectation. Also we define the degree of pessimism or optimism, in the same way as (Hwang & Salmon, 2013).

$$s_{it} = \frac{\delta_{it}}{E_t(r_{mt})}, \quad s_{mt} = \frac{\delta_{mt}}{E_t(r_{mt})}$$ [2]

In order to model the asymmetric biases in betas, we follow Hwang and Salmon (2013) and assume that s_{it}^* is composed of market sentiment s_{mt}, the asymmetric biases[3] from cross-sectional mispricing $h_{mt}(1-\beta_{imt})$, and idiosyncratic disturbance ω_{it},

[1] The bias can either be negative or positive depending on the events in financial history.
[2] The degree of pessimism is calculated by measuring the impact of sentiment and cross-sectional mispricing on market portfolio.
[3] Following Hwang and Salmon (2005) we argue that at any given time the individual assets' betas as biased, governed by herding towards market, termed as "beta herding".

$$\frac{E_t^b(r_{it})}{E_t(r_{mt})} = \beta_{imt}^b = \beta_{imt} - h_{mt}(\beta_{imt} - 1)$$

Where $E_t^b(r_{it})$ denotes biased asset returns, $E_t(r_{mt})$ denotes the market returns, h_{mt} is a parameter which accounts for adverse and rational herding in the market, β_{imt}^b and β_{imt} represent biased and true betas respectively.

$$s_{it}^{*} = s_{mt} + h_{mt}(1-\beta_{imt}) + \omega_{it}$$

Where it is expected $E_c(s_{it}^{*}) = E_c(s_{mt} - h_{mt}(\beta_{imt} - 1) + w_{it}) = s_{mt}$, since $E_c(\beta_{imt} - 1) = E_c(w_{it}) = 0$. We substitute s_{it}^{*} from above equation and write δ_{it} as,

$$\delta_{it} = [s_{mt} + h_{mt}(1-\beta_{imt}) + \omega_{it}] * [E_t(r_{mt})]$$

segregating parametric terms on the basis of their characteristic nature. Thus,

$$\delta_{it} = s_{mt}E_t(r_{mt}) + h_{mt}(1-\beta_{imt})E_t(r_{mt}) + \omega_{it}E_t(r_{mt})$$

In the above expression the first two terms constitute the sentiment and herding factor, respectively and υ_{it} represents the idiosyncratic disturbances. Hence, we can have a measure of bias due to irrational dynamics in asset prices. Finally, the returns equation can then be written as:

$$E_t^{s}(r_{it}) = E_t(r_{it}) + s_{mt}E_t(r_{mt}) + h_{mt}(1-\beta_{imt})E_t(r_{mt}) + \upsilon_{it}$$

$$E_t^{s}(r_{it}) = 3F.F.\,factors + Factor_1 + Factor_2 + \upsilon_{it}$$ [4]

We interpret $Factor_1$ and $Factor_2$ as fluctuations in the market sentiment and herding due cross-sectional mispricing or bias in the asset returns due to the above mentioned factors. Also, we assume that the idiosyncratic variances are constant and time-invariant.

[4] $Factor_1 = s_{mt}E_t(r_{mt})$, $Factor_2 = h_{mt}(1-\beta_{imt})E_t(r_{mt})$. $3F.F.\,factors$ refers to conventional three Fama and French factors, it represents individual excess portfolio returns when there is no herding or market sentiment observed.

2.1 Dynamic Factor Model

We incorporate the above intuition by augmenting the model proposed by He, Huh, & Lee, (2010), introducing two (in addition in addition to the three conventional Fama and French factors already defined, market, size and value) latent variables which constitute the bias i.e. market sentiment and herding due to cross-sectional mispricing.

Assuming a vector $R_t = \left[R_{BH,t} R_{BM,t} R_{BL,t} R_{SH,t} R_{SM,t} R_{SL,t} R_{m,t} \right]$, represents the six excess demeaned portfolio returns sorted based on size (B, S) and values (H, M , L) and one additional excess market return (m) . Let $F_t = [F_{mkt} F_{size} F_{btm} F_{sent} F_{herd}]$ denote a vector of zero-mean unobserved state/latent variables. $Factor_1$ and $Factor_2$ (from the previous section) are represented as F_{sent} and F_{herd}, respectively. Thus, the measurement equation in its matrix form looks like:

$$\begin{pmatrix} R_{BH,t} \\ R_{BM,t} \\ R_{BL,t} \\ R_{SH,t} \\ R_{SM,t} \\ R_{SL,t} \\ R^{s}_{m,t} \end{pmatrix} = \begin{pmatrix} \lambda_{1,1} & \lambda_{1,2} & \lambda_{1,3} & \lambda_{1,4} & \lambda_{1,5} \\ \lambda_{2,1} & \lambda_{2,2} & \lambda_{2,3} & \lambda_{2,4} & \lambda_{2,5} \\ \lambda_{3,1} & \lambda_{3,2} & \lambda_{3,3} & \lambda_{3,4} & \lambda_{3,5} \\ \lambda_{4,1} & \lambda_{4,2} & \lambda_{4,3} & \lambda_{4,4} & \lambda_{4,5} \\ \lambda_{5,1} & \lambda_{5,2} & \lambda_{5,3} & \lambda_{5,4} & \lambda_{5,5} \\ \lambda_{6,1} & \lambda_{6,2} & \lambda_{6,3} & \lambda_{6,4} & \lambda_{6,5} \\ \lambda_{7,1} & \lambda_{7,2} & \lambda_{7,3} & \lambda_{7,4} & \lambda_{7,5} \end{pmatrix} \begin{pmatrix} F_{mkt,t} \\ F_{size,t} \\ F_{btm,t} \\ F_{sent,t} \\ F_{herd,t} \end{pmatrix} + \begin{pmatrix} \upsilon_{BH,t} \\ \upsilon_{BM,t} \\ \upsilon_{BL,t} \\ \upsilon_{SH,t} \\ \upsilon_{SM,t} \\ \upsilon_{SL,t} \\ \upsilon_{m,t} \end{pmatrix}$$

We assume that the unobserved state variables follow an autoregressive process of order 1 i.e. AR(1) process[5]. The transition equation when expressed in matrix form looks like:

[5] This assumption follows from the model used by Stock & Watson, 1988 in their study. Where they use a dynamic factor model to formulate a co-incident index on inflation. Further, we put the same restrictions on latent variables as directed by Stock & Watson.

$$\begin{pmatrix} F_{mkt,t} \\ F_{size,t} \\ F_{btm,t} \\ F_{sent,t} \\ F_{herd,t} \end{pmatrix} = \begin{pmatrix} \phi_1 & 0 & 0 & 0 & 0 \\ 0 & \phi_2 & 0 & 0 & 0 \\ 0 & 0 & \phi_3 & 0 & 0 \\ 0 & 0 & 0 & \phi_4 & 0 \\ 0 & 0 & 0 & 0 & \phi_5 \end{pmatrix} \begin{pmatrix} F_{mkt,t-1} \\ F_{size,t-1} \\ F_{btm,t-1} \\ F_{sent,t-1} \\ F_{herd,t-1} \end{pmatrix} + \begin{pmatrix} \xi_{mkt,t} \\ \xi_{size,t} \\ \xi_{btm,t} \\ \xi_{sent,t} \\ \xi_{herd,t} \end{pmatrix}$$

We can represent the same matrix equations as a state space representation:

$$R_t = \lambda F_t + \upsilon_t$$

$$F_t = \phi F_{t-1} + \xi_t$$

Where υ_t and ξ both follow joint normal distributions, with the following restrictions:

$$\upsilon_t \sim i.i.d.N(0, \mathbb{Z})$$

$$\xi_t \sim i.i.d.N(0, \mathbb{Q})$$

$$E\left[\upsilon_t \xi_\tau^{'}\right] = 0$$

for all t and τ . Where, $\mathbb{Z} \equiv diag\left[\sigma_{BH}^2 \sigma_{BM}^2 \sigma_{BL}^2 \sigma_{SH}^2 \sigma_{SM}^2 \sigma_{SL}^2 \sigma_M^2\right]$ is (7x7) co-variance matrix of idiosyncratic disturbances in portfolio and market returns. We identify the covariance matrix $\mathbb{Q}$ as a (5x5) identity matrix with no considerable implications on the results. λ denotes a vector of factor loadings of different factors on the asset portfolio returns, restrictions imposed on λ are discussed in the next section.

2.2 Factor Identification

The number of free parameters which can be estimated, given our order of state space structure, is given by $n(n+1)/2$ where n denotes the number of elements in vector R_t. This includes variance of disturbances in the measurement equation and coefficients of measurement as well as the transition equation. We normalize disturbances of the transition equation to one as suggested by Stock & Watson, 1988.

To obtain identification, some factor loadings are restricted for a set portfolios depending upon the nature of the factors under study. The first column is determined by the market factor which has a different impact on every individual portfolio and we assume the loading on market returns as one.

$$\lambda_{1,1} = \beta_{mBH} \text{ , } \lambda_{2,1} = \beta_{mBM}$$
$$\lambda_{3,1} = \beta_{mBL} \text{ , } \lambda_{4,1} = \beta_{mSH}$$
$$\lambda_{5,1} = \beta_{mSM} \text{ , } \lambda_{6,1} = \beta_{mSL}$$
$$\lambda_{7,1} = 1.0$$

The second column pertains to the size factor. The impact of the size factor will have a common effect on all the individual portfolio returns of the same size. Hence, we have a common parameter for stocks with same size. As per our data we have two sets of portfolios on the basis of size i.e. big or small.

$$\lambda_{1,2} = \lambda_{2,2} = \lambda_{2,2} = \beta_B \text{, } \lambda_{4,2} = \lambda_{5,2} = \lambda_{6,2} = \beta_S$$
$$\lambda_{7,2} = 0.0$$

Similarly, third column accounts the value factor or portfolios sorted on the basis of book-to-market ratio. We select a common parameter for stocks with same value. The data marks three sets of portfolios on btm ratio High, Medium and Low. Each category will have a different factor loading.

$$\lambda_{1,3} = \lambda_{4,3} = \beta_{vH} \ , \ \lambda_{2,3} = \lambda_{5,3} = \beta_{vM} \ , \ \lambda_{3,3} = \lambda_{6,3} = \beta_{vL}$$

$$\lambda_{7,3} = 0.0$$

Fourth, we assume that all individual portfolio returns will have a similar sensitivity towards the market sentiment. Thus, we take a common factor loading for all. Also, the sentiment factor will have a lasting effect on the excess market returns. Hence, the restrictions will look like:

$$\lambda_{1,4} = \lambda_{2,4} = \lambda_{3,4} = \lambda_{4,4} = \lambda_{5,4} = \lambda_{6,4} = \beta_{sent}$$

$$\lambda_{7,4} = \beta_{msent}$$

The last factor accounts for herding by cross-sectional mispricing of the betas. We assume that the related sensitivities do not vary amongst the same valued stocks. Therefore, we adopt a similar pattern for factor loadings on herding factor as in the value factor. Further we assume that the market returns is not impacted by the herding factor.

$$\lambda_{1,5} = \lambda_{4,5} = \beta_{herdH} \ , \ \lambda_{2,5} = \lambda_{5,5} = \beta_{herdM} \ , \ \lambda_{3,5} = \lambda_{6,5} = \beta_{herdL}$$

$$\lambda_{7,5} = 0.0$$

The estimation of the free parameters is done using the Kalman filter. We use unconditional mean and variance matrices to initialize the filter[6].

3. Data

Our unique sample includes data from the financial crisis period 2007-2008 which helps us better understand and distinguish factors on herding and fundamentals. The model uses six, size and BTM sorted, Fama & French (1993) portfolios pertaining to the Indian Context from 2007 to

[6] For further study, the reader can refer to Chang-Jin & R.Nelson, 1999.

2015. The excess individual portfolio returns for India are constantly managed and updated by (Agarwalla, Jacob, & Varma, 2013). They use the same methodology as used by (Fama & French, Common risk factors in the returns on, 1993) to construct similar portfolios dedicated to the Indian Capital Markets. As herding is understood to be short termed phenomena we consider using daily returns data. Also, as Agarwalla, Jacob, & Varma (2013) suggest, we use a survivorship biased data to run our analysis. This helps us eliminate any companies which have shut down their business in the interim periods.

4. Results and Interpretation

A detailed account of estimated parameters is given in table 1. It could be easily noticed that the market factor has a positive impact on all the individual portfolio returns.

Table 1: Estimated Parameters: Coefficients of Measurement Equation

Parameter	Coefficient	T-Stat	Significance level	Parameter	Coefficient	T-Stat	Significance level
β_{mBH}	0.933511256	48.46685	***	β_{mBL}	0.978298117	36.96697	***
β_{B}	0.693289165	59.66258	***	β_{vL}	0.520268161	26.07661	***
β_{vH}	-0.041871429	-17.73565	***	β_{herdL}	-0.034430658	-1.70326	*
β_{sent}	1.443627338	57.6862	***	β_{mSH}	0.865518865	257.07	***
β_{herdH}	0.003987347	1.66166	*	β_{S}	-0.080790904	-43.6683	***
β_{mBM}	1.053839154	50.94162	***	β_{mSM}	1.642802073	116.15477	***
β_{vM}	0.193562755	24.44922	***	β_{mSL}	1.772946489	40.2612	***
β_{vL}	0.004189998	0.3989	N.S	β_{msent}	1.443903198	56.9283	***

Table 2 : Estimated Parameters : Variance of Disturbances in the Measurement Equation

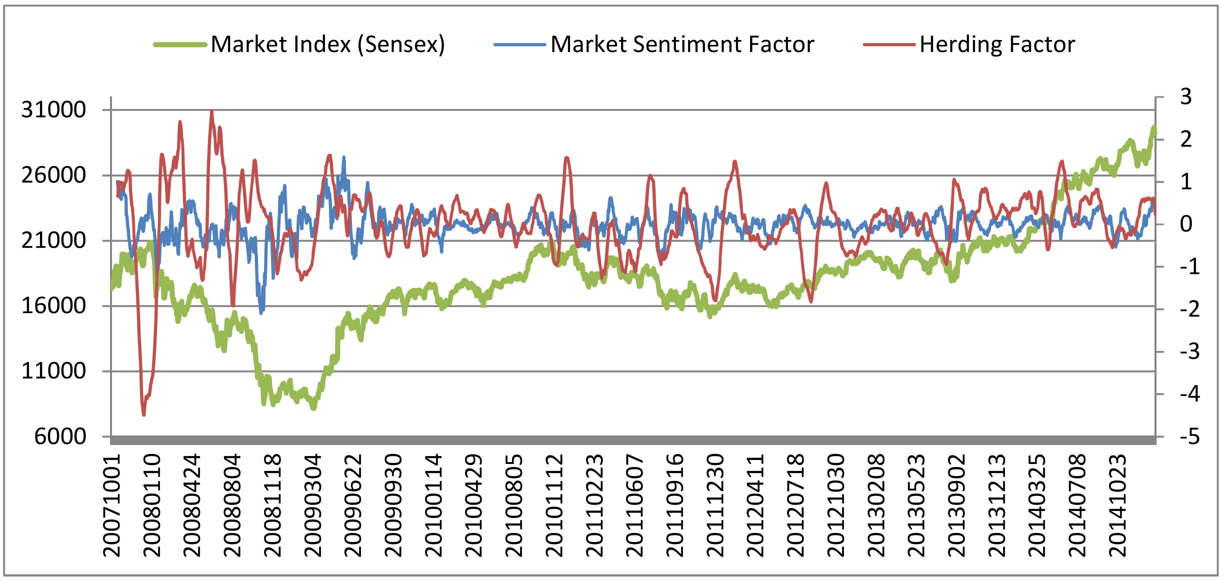
Parameter	Coefficient	T-Stat	Significance level
σ^2_{SL}	0.187078281	16.92637	***
σ^2_{SM}	0.256782934	37.33553	***
σ^2_{SH}	0.188452052	4.96641	***
σ^2_{BL}	0.00000129	1.21E-04	N.S
σ^2_{BM}	0.29496142	50.11755	***
σ^2_{BH}	1.505796074	59.95169	***
σ^2_{M}	0.000000343	-5.66E-05	N.S

Table 3 : Estimated Parameters : Coefficients of Transition Equation

Parameter	Coefficient	T-Stat	Significance level
ϕ_1	0.092118781	3.76235	***
ϕ_2	0.107104676	4.32716	***
ϕ_3	0.324135922	10.72688	***
ϕ_4	0.103791661	4.32227	***
ϕ_5	0.896951585	20.41733	***

The coefficient of market sentiment is positive for both individual portfolio returns as well as the market returns with a high significance level, proving that market inefficiencies are a consequence of changing market-wide sentiment. The herding factor also proves to be significant at 10% level for high and low valued individual portfolio returns. Where, it positively impacts the high valued stocks and negatively on low valued stocks.

Figure 1[7] Herding and Sentiment against the Market Index



In Figure 1 we plot the market sentiment factor and the herding factor alongside market index. During the Global Financial Crisis 2007-2008, the time when investors were apprehensive of the markets, we see adverse herding at the starting and a fluctuating market sentiment pointing at mispricing of individual returns.

[7] The x-axis represents the time or date in the financial history, where for eg. 20071001 signifies 1st day of October in year 2007.

The herding factor seems to subside in the late 2008 when adverse effects of the financial crisis gripped the international markets. Market sentiment still shows some persistency till the end of 2009. These results reveal that the investors tend to fall back to their fundamentals in the period of crisis, even when the market sentiment is strong. We also notice that after late 2009 the market sentiment as well as adverse herding tends to fade away slowly leading to economic recovery. Literature proposes that some kind of herding is always present in the market, herding observed beyond 2010 could be termed as "rational herding", which contribute to markets behaving efficiently.

Further using a year on year sample we re-estimate the model and table 4 reports the significance level of market sentiment and herding factors across the years. It could be seen that the sentiment factor affects the markets irrespective of any financial events, whereas, the herding factors tend to disappear or become less significant after 2012.

Table 4: India Results: Test for persistency in sentiment and herding factor[8]

Year	Sentiment	HHV	HMV	HLV
2008	Y	Y	Y	Y
2009	Y	0	Y	Y
2010	Y	Y	Y	Y
2011	Y	Y	Y	Y
2012	Y	0	Y	0
2013	Y	0	0	0
2014	Y	0	0	0

Note: Where Y denotes the significance of the variable

To test the applicability of the model in other markets, we run the same model on the NYSE Index for the US context. The results give us interesting insights into the herding behavior prevalent in the US markets.

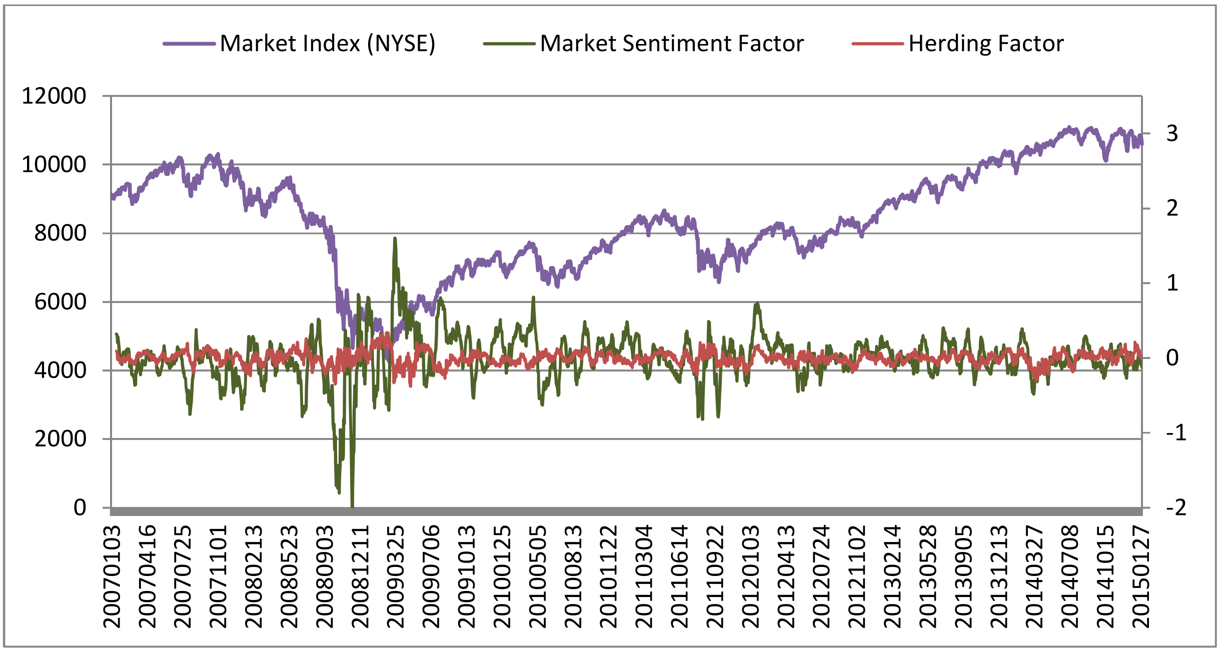
[8] We observe that sentiment takes a toll on returns irrespective of any financial events happening across time. However the nature of impact is specific to the duration we are considering. Herding factor seems to influence the mid valued stocks more than any other range. Where HHV denotes herding influence on High Valued Stocks.

Table 5: US Results: Test for persistency in sentiment and herding factor

	Sentiment	HHV	HMV	HLV
2008	Y	Y	Y	Y
2009	Y	Y	Y	Y
2010	Y	Y	Y	Y
2011	Y	Y	Y	0
2012	Y	Y	Y	Y
2013	Y	Y	Y	0
2014	Y	0	Y	0

Note: Where Y denotes the significance of the variable

Figure 2[9] Herding and Sentiment against the Market Index



Our results show that herding is a more persistent phenomenon in the US markets than in the Indian context whereas the sentiment is equally significant in both Indian as well as the US markets. But the herding factor affects the pricing of assets more significantly in Indian markets than in the US.[10]

[9] The x-axis represents the time or date in the financial history, where for eg. 20071001 signifies 1st day of October in year 2007.
[10] Parameter estimates for US markets can be provided on request.

5. Conclusion

Using an augmented standard three factor CAPM model, the paper successfully demonstrates that fluctuations in asset prices are also influenced by market wide sentiment and behavioral aspects of investors such as herding. It is evidenced that these factors have played an influential role in market movements around the 2007-2008 financial crisis. We conclude that a developing economy is more prone to behavioral factors which have a direct impact on asset pricing, as is evident from the fluctuating nature of the factors in the case of India. Whereas in a developed economy (US) people make informed decisions and herding though persistent, has a lower magnitude with minimal bias.

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